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RESEARCH

Socio-economic Development and Carbon Productivity: A Panel Data Analysis of the World's Largest Carbon-Emitting Countries

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Abstract

As global concerns about climate change intensify, assessing the environmental efficiency of production processes through carbon productivity has become increasingly important. This study examines the impact of socio-economic development on carbon productivity in the top 18 CO2-emitting countries, which contribute approximately 82% of global CO2 emissions, over the period 1990–2019. Using a class of econometric tests to address heterogeneity and cross-sectional dependence, we employ the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model for final estimation, ensuring robustness with Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG) estimations. The empirical findings reveal that GDP per capita, Trade, and FDI increase carbon productivity while energy consumption and urbanization curtail carbon productivity. The country-specific effects indicated that 83% of the sample countries exhibit positive relationships between socio-economic development and carbon productivity, suggesting that these nations can serve as models for effective low-carbon policies. Moreover, the results demonstrate bi-directional relationships for GDP per capita, FDI, and energy use with carbon productivity and uni-causal relationship for trade and urbanization. The study highlights the need for implementing stricter regulations to improve energy efficiency and promote the adoption of renewable energy sources such as wind, solar, hydro, and nuclear power. Additionally, countries should incentivize green technology investments through tax breaks and subsidies, enhance international trade agreements that support the exchange of clean technologies, and develop sustainable urban planning initiatives to mitigate the negative impact of urbanization on carbon productivity.

Keywords Carbon productivity · Socio Economic development · World's largest carbon emitting countries · Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL)

1 Introduction

Since the twentieth century, global warming is a pressing global issue that has acquired extensive attention from scientists, policymakers, and the international community [1, 2]. Greenhouse gases, particularly CO2, have been identified as the primary drivers of climate change [3, 4]. The Annual Greenhouse Gas Index (AGGI) from NOAA indicates that between 1990 and 2022, the radiative forcing effect on the climate from long-lived greenhouse gases increased by 49%, with CO2 contributing approximately 78% of this increase [5]. The global trends show that most of countries are not able to achieve targeted economic growth without an increase in CO2 emissions [6]. Keeping in view the severity of this situation, reducing CO2 emission is a salient objective in policymaking around the globe. To achieve this objective, it is important to understand the relationship between socio-economic development and environmental sustainability. Extensive scientific research has highlighted that energy consumption is the predominant source of CO2 emissions, linking it directly to industrial activities and economic growth [7]. This correlation underscores the complexity of addressing climate

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change, as efforts to reduce carbon emissions must consider the implications for global economic stability and development [8]. Consequently, the reduction of carbon emissions, especially those related to energy consumption, has become a critical focus for international climate policies, which aim to mitigate the adverse effects of climate change while sustaining economic growth [9].

The issue of increasing CO2 emissions is leading to tracking the global emissions hotspots, which was not an essential concern before the industrial revolution. The CO2 emissions were 280 ppm, and after the industrial revolution, they surpassed 410 ppm [10]. Therefore, it is necessary to target the countries which are responsible for this situation. In this regard, top 18 largest carbon-emitting countries collectively contribute approximately 82% of the world's total CO2 emissions, making them critical players in the global effort to address issue of climate change. These countries, which include major economies such as the United States, China, India, Russia, and Japan, face the dual challenge of achieving significant energy conservation and emission reductions while maintaining economic growth and development [11]. For instance, China is the largest CO2 emitter, contributing 30.9% of global emissions, while the USA contributes 13.5%, India 7.3%, Russia 4.7%, and Japan 2.9% of world's total emissions [12]. In this way, many of these nations are at various stages of industrialization and urbanization, leading to a high correlation between carbon emissions and economic activities. This complex relationship presents a dilemma for policymakers who must balance the urgent need for carbon reduction with the imperatives of economic development and poverty alleviation [13]. Given their substantial impact on global emissions, these countries are pivotal in the transition to a low-carbon economy, which seeks to harmonize economic development with environmental sustainability.

The efforts made by countries to address climate change can be assessed through carbon productivity [14]. The concept of carbon productivity, introduced by Kaya and Yokobori [15], serves as an important indicator for evaluating the efficiency with which economic output is generated relative to carbon emissions. It measures the ratio of output produced to CO2 emissions, offering valuable insights into a nation's emission performance over time [16]. This concept is crucial in the context of achieving the Intergovernmental Panel on Climate Change's (IPCC) ambitious targets for greenhouse gas reductions by 2050, which require a substantial increase in carbon productivity globally [17]. The transition to a low-carbon economy is crucial, and carbon productivity integrates the two primary targets of this transition. The first target is to maintain economic development, and the second is to reduce CO2 emissions [18]. Therefore, increasing carbon productivity paves the way toward achieving a low-carbon economy by balancing these two essential goals. The top 18 carbon-emitting countries, due to their significant share of global emissions, have a profound potential to influence these targets. By focusing on carbon productivity, these nations can develop strategies to decouple economic growth from carbon emissions, ensuring sustainable development [17]. This approach not only aids in meeting international climate goals but also enhances economic resilience and technological innovation.

Understanding how various socio-economic development factors impact carbon productivity is critical for designing effective environmental and economic policies. Factors such as GDP per capita, trade openness, foreign direct investment (FDI), energy consumption, and urbanization play significant roles in shaping carbon productivity [16]. For instance, it is argued that higher GDP per capita often correlates with greater technological advancements and efficiency, potentially increasing carbon productivity [19, 20]. Trade openness and FDI can facilitate the transfer of cleaner technologies and sustainable practices across borders, enhancing carbon efficiency [21, 22]. Conversely, high energy consumption, particularly from non-renewable sources, and rapid urbanization can lead to increased emissions, thereby reducing carbon productivity [23, 24]. Studying these interactions is essential because it helps to identify leverage points for improving carbon productivity while sustaining economic growth. By locating which factors most significantly influence carbon productivity, policymakers can adapt interventions to maximize positive impacts and mitigate negative ones, thus fostering a more sustainable and resilient economic development pathway.

Despite the increasing attention to carbon productivity and its implications for sustainable development, there exist limited empirical studies exploring relationship between socio-economic development and carbon productivity. Moreover, existing studies have predominantly been case-specific, often focusing on individual countries or regions (e.g., [16, 19, 25]). These studies have provided mixed results, with some indicating positive relationships between socio-economic factors and carbon emissions (e.g., [24], while others suggest negative or inconclusive outcomes (e.g., [26]. Moreover, prior research has frequently employed a confined range of socio-economic factors, thereby overlooking the need for a broader and more integrated assessment [21]. This lack of comprehensive analysis is particularly evident when considering the world's largest carbon-emitting countries, which are responsible for around 82% of global carbon emissions. By focusing on these top 18 carbon-emitting nations, this study aims to fill a critical knowledge gap by offering a more generalized and globally representative understanding of how various socio-economic factors influence carbon productivity. Such an approach not only enhances the applicability of the findings across different contexts but also provides a global perspective that can better inform international policy-making and collaborative efforts to oppose climate change.

As a contribution to the existing body of literature and the ongoing discourse on the environmental consequences of socio-economic development, this study employs a panel dataset for the 18 largest carbon-emitting countries covering the period from 1990 to 2019 to investigate the relationship between socio-economic development and carbon productivity. The empirical findings offer valuable insights that could guide policymakers and stakeholders in the region about the implications of socio-economic development on carbon productivity and environmental sustainability. Moreover, the findings of the study contribute to national and global efforts aiming at achieving SDG 13 (Climate Action), which emphasizes urgent actions to minimize the negative consequences of climate change and its impacts by improving carbon productivity and fostering sustainable development practices in the world's largest carbon-emitting countries. Furthermore, the results emphasize the need for proactive measures and policy interventions that prioritize sustainable development and promote low-carbon development strategies in these countries to mitigate the adverse effects of socio-economic development on the environment.

2 Review of Existing Literature and Contribution Margins

2.1 Theoretical Perspectives

The relationship between socio-economic development and carbon productivity is multifaceted and has been approached from various theoretical and empirical perspectives. From a theoretical standpoint, one prominent theory is the Environmental Kuznets Curve (EKC), which suggests that environmental degradation follows an inverted U-shape as a country's income level increases which means that environmental degradation initially increases with economic growth but decreases after reaching a certain income level [27, 28]. This theory has been extensively discussed and tested in relation to carbon emissions as a specific form of environmental impact [29–31]. The EKC points out that as economies develop, they transition from manufacturing-based to service-oriented structures, which are less carbon-intensive [32, 33]. Another critical theory is the Theory of Ecological Modernization, which argues that technological advancement and institutional changes can lead to environmental improvements alongside economic growth [34]. This theory supports the idea that investments in green technologies and innovation are important in improving carbon productivity, implying a decoupling of economic growth from carbon emissions [35]. Conversely, the studies conducted by Liu et al. [36] and Marcotullio & Lee [37] support the perspective of the urban environmental transition theory, which posits that the environmental impact intensifies as nations evolve into manufacturing-based economies accompanied by urban expansion.

Moreover, the concept of sustainable development highlights much of the discussion on carbon productivity. It emphasizes the need to balance socio-economic advancement with environmental preservation to ensure long-term ecological and human well-being [38, 39]. The Brundtland Report [40] provided the foundational framework for this, defining sustainable development as development that meets the needs of the present without compromising the ability of future generations to meet their own needs [40, 41]. Recent studies have built on these theories to explore the nonlinear impacts of socio-economic development on carbon productivity. For example, Wang et al. [20] analyzed the effects of economic development on carbon productivity using advanced econometric models. They found that economic growth has a significant, though nonlinear, positive impact on carbon productivity in Hubei, China, indicating different stages of economic development influence carbon productivity in varying ways. Furthermore, the comprehensive review by Mardani et al. [19] underscores the critical relationship between CO2 emissions and economic growth, illustrating how this relationship shapes policymaking in energy management and sustainability. Their findings emphasize that both economic growth and CO2 emissions are interlinked, where increases in one tend to stimulate changes in the other, suggesting that policy interventions aimed at reducing emissions could also impact economic performance.

2.2 Empirical Evidence

Empirically, recent studies have adopted diverse methodologies to analyze the impacts of socio-economic development on carbon emissions. For instance, Li et al. [42] investigated the effects of socio-economic productive capacity on renewable energy development across the BRICS nations. Utilizing panel ARDL and QARDL models, they found that variables such as national income, financial development, and productive capacity positively influence renewable energy development in the long run, highlighting the role of socio-economic development in fostering an environment conducive to renewable energy usage, which in turn can enhance carbon productivity [20, 43]. Another study from Marbuah et al. [44] examined the relationship between social capital and carbon emissions in Swedish counties. Their findings reveal that high levels of social capital are associated with reduced emissions, indicating that strong communal ties and trust can foster behaviors and policies that result in lower carbon emissions.

In a broader scope, Alotaibi & Alajlan 26 analyzed the association between socio-economic indicators like the human development index (HDI) and carbon dioxide emissions in G20 countries under the EKC framework. Using quantile regression, they presented that socio-economic development, as captured by HDI, tends to reduce CO2 emissions across various quantiles, thereby supporting the EKC hypothesis. In a similar way, study by Jahanger et al. [45] explores the N-shaped EKC in leading nuclear energy-producing nations, revealing that nuclear energy, while supporting economic growth, offers mixed environmental impacts. Their findings suggest the importance of integrating nuclear with renewable energy sources to balance economic development with environmental sustainability [46]. Moreover, study by Raihan & Tuspekova [24] on the nexus between economic growth, energy use, agricultural productivity, and carbon emissions in Nepal found that while economic growth and traditional energy use increase emissions, renewable energy use and improved agricultural productivity contribute to emission reductions.

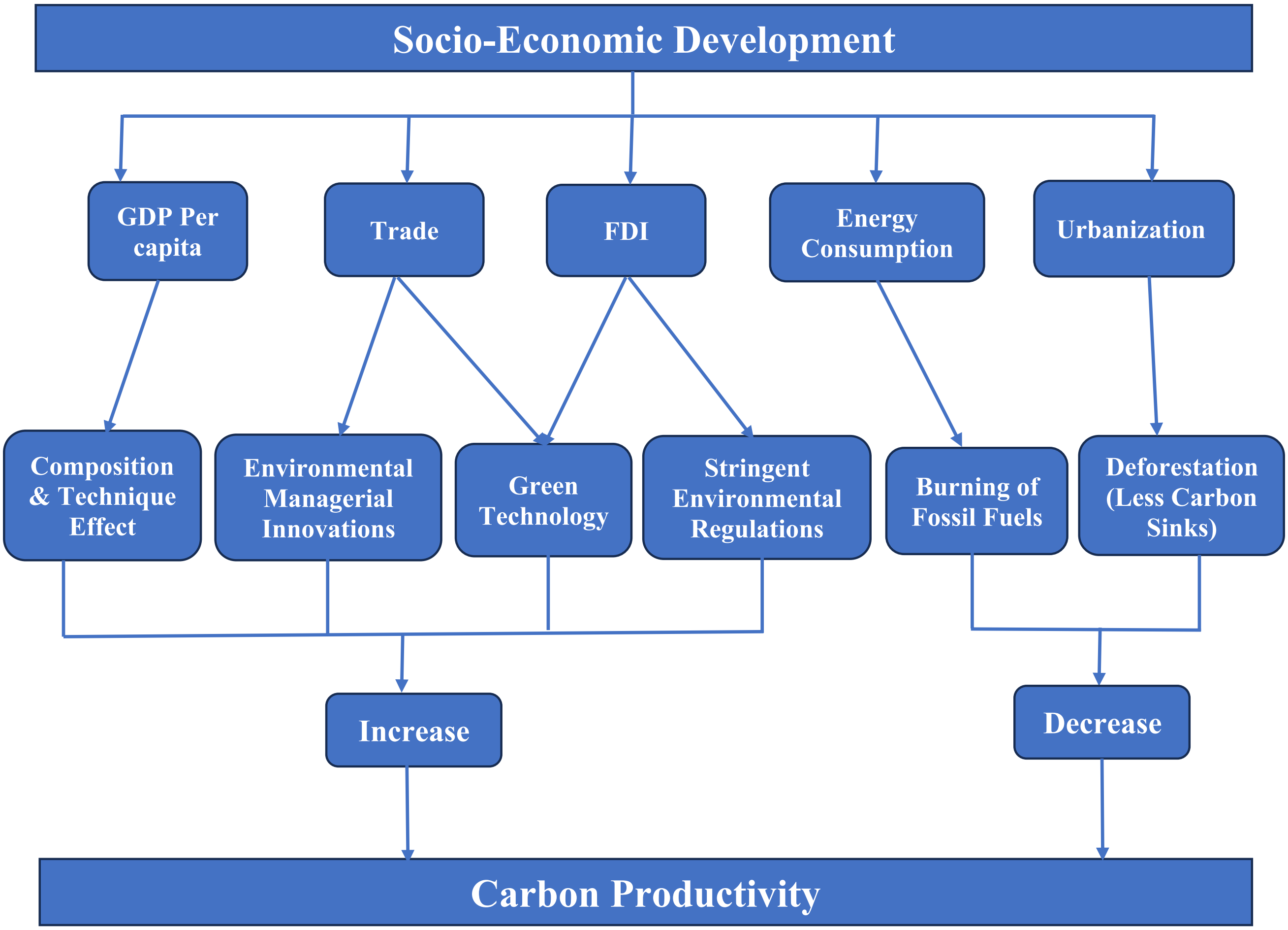
2.3 Literature Gap and Contribution of the Study

The previous literature explored the impact of socio-economic development on various environmental degradation metrics, such as CO2 emissions and carbon intensity (e.g., [22, 23, 47], and delves into the connections between urbanization, foreign direct investment (FDI), renewable energy, net trade, economic growth, carbon emissions, and environmental sustainability (e.g., [24, 43, 48]. However, the findings regarding socio-economic development's effect on CO2 emissions are inconclusive and mixed. While certain studies show a positive link between socio-economic development and CO2 emissions (e.g., [24, 49], others demonstrate negative or inconclusive relationship (e.g., [26]. Moreover, there is limited literature available on carbon productivity in relation to socio-economic development. The existing research on carbon productivity is generally narrowed to specific national contexts or a confined range of socio-economic factors. For instance, Hu & Liu [25] focused exclusively on Australia, assessing the impact of technological innovation on carbon productivity between 1990 and 2012. Similarly, Zhang & Xu [50] explored how environmental regulations affect carbon productivity, while Li & Wang [16] considered a variety of socio-economic factors in China, utilizing spatial analysis to reveal how elements like growth, technology, and FDI contribute to increasing carbon productivity, whereas factors like population and urbanization may hinder it. These studies, while insightful, illustrate the limitations of current research which predominantly revolves around case-specific analyses, inconclusive and mixed results, and overlooks a broader, more integrated assessment of carbon productivity's role in fostering a low-carbon economy amidst sustainable growth.

Both theoretical propositions and empirical evidence suggest that socio-economic development has diverse environmental effects, encompassing both detrimental and beneficial features, depending on a suite of sociodemographic, economic, environmental, and institutional factors [19, 47]. This implies the necessity for targeted and more disaggregated analyses that account for the unique characteristics and contexts of specific socio-economically and environmental regions. However, until now, there remains a critical need for targeted empirical studies that focus specifically on the world's largest carbon emitters. That is, the policy discussion on socio-economic development in leading carbon emitters has been without solid evidence despite the presence of both obstacles and opportunities associated with socio-economic development [51]. The lack of reliable evidence and empirical studies on the association between socio-economic development and carbon productivity in world's largest carbon emitters creates critical knowledge gaps that hinder the development of effective policies and informed decision-making concerning the sustainable development, which deters the ability of governments to tackle the difficulties and maximize the advantages brought by socio-economic development. Our study addresses these gaps by providing a detailed empirical analysis of the 18 highest-emitting countries, which collectively account for 82% of the global emissions. This focus is critical as it offers insights that are directly applicable to the nation's most responsible for climate change, thus providing a foundation for policy interventions that are both impactful and tailored to the specific economic and environmental contexts of these key countries.

3 Conceptual Framework

Socio-economic development can influence the carbon productivity in two different ways. For instance, some socio-economic factors such as GDP per capita, Trade, and FDI can improve the carbon productivity through the composition effect, technique effect, and by introducing innovative technologies [47]. On the other hand, some other socio-economic factors, such as energy consumption and urbanization, can have negative consequences on carbon productivity [23]. For example, increased energy consumption negatively impacts environmental quality though the use of energy-intensive industries and infrastructure. Moreover, in most of the countries, electricity production is mainly fueled by coal and other non-renewable sources [7]. Consequently, burning of fossil fuels increase CO2 emissions which reduce carbon



Source: Authors' formulation

Fig. 1 Underlying mechanism of hypothesized relationship

productivity. The Fig. 1 describes the channels through which socio-economic development can affect carbon productivity.

In a similar way, increasing urbanization has a negative impact on the environment. As urbanization continues, its rapid expansion demand for energy and resources from industries and other economic sectors grows significantly and places immense strain on existing infrastructure, leading to congestion, inadequate transportation systems, and overwhelmed utilities such as water and sanitation [52]. Moreover, the uncontrolled growth of urban areas contributes to environmental degradation through land use changes and encroachment on agricultural land, deforestation, and increased pollution from industrial activities and transportation [53]. Conversely, increasing GDP per capita can improve carbon productivity through the economic efficiency. The EKC suggests that when GDP per capita crosses the threshold level, environmental quality improves due to shifting to a knowledge-based economy [28]. Similarly, according to the Pollution Halo hypothesis, FDI can brings positive changes in the environmental management system and introduce environment-friendly technology in the host country. Green technology will replace obsolete technology, which will reduce pollution and promote environmentally friendly practices that will help in increasing carbon productivity [54]. Moreover, trade can benefit the environment as it serves as an engine of technological progress due to the technological spillovers it generates. In an open economy, technological progress also depends on technological spillover other than domestic research and development spending [22].

4 Material and Methods

4.1 Data and Variables

The study utilized a secondary-source panel dataset covering the period from 1990 to 2019 for the 18 largest carbon-emitting countries, with data sourced from the World Development Indicators (WDI). The countries comprise China, United States of America (USA), Japan, India, Germany, the United Kingdom, France, Italy, Poland, Ukraine, Mexico, South Korea, Australia, Brazil, Saudi Arabia, Spain, and Indonesia. The

Table 1 Descriptive statistics

Variables	Symbol	Measurement unit	Mean	Std. Dev	Minimum	Maximum
Carbon productivity	$C_{i,t}$	$\frac{GDP}{CO_2 emissions}$	2835148	524736.1	2253962	4207909
GDP per capita	$G_{i,t}$	Constant 2010 US$	20121.24	2427.796	16587.6	24259.65
Energy use	$E_{i,t}$	kg of oil equivalent per capita	3115.564	462.0148	2732.867	4650.382
FDI net	$F_{i,t}$	BoP, current US$	-2.38×10^9	6.69×10^9	-1.53×10^{10}	1.13×10^{10}
Net trade	$T_{i,t}$	BoP, current US$	1.54×10^{10}	1.10×10^{10}	-2.76×10^9	3.75×10^{10}
Urban population	$U_{i,t}$	% of total population	9.63×10^7	1.89×10^7	6.68×10^7	1.29×10^8

Number of observations = 540

variables are selected based on previous studies on the nexus between socio-economic development and carbon productivity (e.g., [19, 26, 47] and their established significance in influencing carbon productivity. GDP per capita is a fundamental indicator of economic performance, with numerous studies demonstrating its critical impact on carbon emissions due to increased industrial activity and energy consumption as economies grow [19, 20]. Urbanization level, often expressed as the percentage of the urban population, is widely recognized as a key factor affecting carbon emissions [23]. It is frequently included in studies examining the relationship between urbanization and environmental impact due to its role in altering energy consumption patterns and increasing infrastructure development (e.g., [43]. The structure and amount of energy use significantly affect carbon productivity. Studies have shown that energy use patterns, especially the reliance on fossil fuels, play a crucial role in environmental degradation (e.g., [24]. Foreign direct investment (FDI) is included due to its potential to transfer cleaner technologies and improve energy efficiency, thus influencing carbon productivity. Previous research has demonstrated significant correlations between FDI and CO2 emissions [21]. Trade openness is another critical factor, as it affects carbon emissions through the scale, composition, and technique effects associated with international trade [22]. Therefore, GDP per capita (constant 2010 US$), energy use (kg of oil equivalent per capita), FDI net (BoP, current US$), net trade in goods and services (BoP, current US$), and urbanization (% of total population) are used as independent variables, while carbon productivity measured as $\left(\frac{\mathrm{GDP}}{\mathrm{CO_2} emissions}\right)$ is the dependant variable**.** It is the amount of CO_2 required to produce a unit of output [15, 16]. However, we used the logarithmic form of the selected variables to linearize the relationship and stabilize the variance. Table 1 presents descriptive statistics of the selected variables.

4.2 Model Specifications

The study used an advanced and robust methodological framework. In the domain of panel data analysis, prior research often neglects crucial aspects such as cross-sectional dependence (CD), slope heterogeneity, and the nuances of causality influences, as noted in studies like Wang et al. [20]. Neglecting factors like cross-sectional dependence could lead to biased and unreliable estimates [55]. To mitigate these issues and address potential endogeneity, our study includes checks for heterogeneity, cross-sectional dependence, and unit root stationarity prior to conducting estimations and causality analysis. The empirical analysis is based on estimating a cross-sectionally augmented autoregressive distributed lag model (CS-ARDL). This model is specifically suitable for heterogeneous panels with cross-sectional dependence [56], and we complement this with robustness checks using mean group estimators such as common correlated effects mean group (CCEMG) and augmented mean group (AMG). Additionally, our study significantly increases the understanding of the socio-economic development's impact on carbon productivity by estimating country-specific effects, providing a detailed and refined analysis at the individual country level. Moreover, the study employs the novel panel granger non-causality testing approach developed by Juodis et al. [57], which enhances our investigation into the directional association between the socio-economic development and carbon productivity in the 18 largest carbon-emitting countries. This methodological approach allows us to overcome limitations of traditional models and provides a more reliable empirical understanding of the dynamics between socio-economic development and carbon productivity. The following functional form contains the selected variables estimated to ascertain the magnitude and direction of the relationship between carbon productivity and socio-economic development.

$$ln\_C_{i,t} = f\left(ln\_G_{i,t}, ln\_E_{i,t}, ln\_F_{i,t}, ln\_T_{i,t}, ln\_U_{i,t}\right),$$

Here, $ln\_C_{i,t}$ is the log transformed carbon productivity, $ln\_G_{i,t}$ represents log of GDP per capita, $ln\_E_{i,t}$ accounts for log of energy use, $ln\_F_{i,t}$ shows log of FDI, $ln\_T_{i,t}$ for log of trade, and $ln\_U_{i,t}$ is the log of urban population. The model in the econometric specification is as follows:

$$ln\left(C_{i,t}\right) = \alpha_i + \beta_{i,1} ln\left(G_{i,t}\right) + \beta_{i,2} ln\left(E_{i,t}\right) + \beta_{i,3} ln\left(F_{i,t}\right) + \beta_{i,4} ln\left(T_{i,t}\right) + \beta_{i,5} ln\left(U_{i,t}\right) + \varepsilon_{it}.$$

The number of cross sections (countries) used in the analysis is denoted by i, whereas the time is represented by t. The α_i represents the intercept term in the model and ε_{it} shows residual term.

4.3 Estimation Methods

4.3.1 Slope Homogeneity Test

To examine the presence of heterogeneity in our sample, we utilize a slope homogeneity test by Swamy [58], who developed the framework to find if slope coefficients of the cointegration equation are homogeneous. Pesaran & Yamagata [59] improved Swamy's slope homogeneity test and formed two $'delta'$ test statistics, $\widetilde{\Delta}$ and $\widetilde{\Delta}_{adj}$:

$$\widetilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\overline{S} - k}{\sqrt{2k}}\right) \sim X_k^2,$$

$$\widetilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\overline{S} - k}{v(T,k)}\right) \sim N(0,1),$$

Where N denotes the number of cross-section units, S account for the Swamy test statistic, and k represents independent variables. If p value of the test is larger than 5%, the null hypothesis is accepted at a 5% significance level, and the cointegrating coefficients are considered homogenous. The $\widetilde{\Delta}$ and $\widetilde{\Delta}_{adj}$ are suitable for large and small samples, respectively, where $\widetilde{\Delta}_{adj}$ is the 'mean–variance bias adjusted' version of $\widetilde{\Delta}$.

Standard delta test $\left(\widetilde{\Delta}\right)$ requires error not to be autocorrelated. By relaxing the assumptions of homoskedasticity and serial independence of Pesaran & Yamagata 59, Blomquist & Westerlund 60 developed a Heteroskedasticity and Autocorrelation Consistent (HAC) robust version of slope homogeneity test,Δ_{HAC} and $\left(\Delta_{HAC}\right)_{adj}$:

$$\Delta_{HAC} = \sqrt{N}\left(\frac{N^{-1}S_{HAC} - k}{\sqrt{2k}}\right) \sim X_k^2,$$

$$\left(\Delta_{HAC}\right)_{adj} = \sqrt{N}\left(\frac{N^{-1}S_{HAC} - k}{v(T,k)}\right) \sim N(0,1).$$

The results of slope homogeneity tests are presented in Table 2. The findings indicate that null hypothesis of slope homogeneity cannot be rejected in the case of Pesaran and Yamagata's (2008) tests because the probability values are larger than 0.05. However, in the case of Blomquist and Westerlund's (2013) tests, the null hypothesis of homogeneous slopes is rejected at a 1% significance level. We rely on the latter, as it is "Heteroskedasticity and Autocorrelation Consistent." Hence, slope coefficients

Table 2 Slope homogeneity tests

Pesaran & Yamagata [59]		
$\widetilde{\Delta}$	$\sqrt{N}\left(\frac{N^{-1}\overline{S}-k}{\sqrt{2k}}\right) \sim X_k^2$	0.200
$\widetilde{\Delta}_{adj}$	$\sqrt{N}\left(\frac{N^{-1}\overline{S}-k}{v(T,k)}\right) \sim N(0,1)$	0.221***
Blomquist & Westerlund [60]		
Δ_{HAC}	$\sqrt{N}\left(\frac{N^{-1}S_{HAC}-k_2}{\sqrt{2k_2}}\right)$	6.092***
$\left(\Delta_{HAC}\right)_{adj}$	$\sqrt{N}\left(\frac{N^{-1}\overline{S}_{HAC}-k_2}{v(T,k)}\right) \sim N(0,1)$	6.722***

*** represents statistical significance at 1%

$\widetilde{\Delta}$ and $\widetilde{\Delta}_{adj}$ represent the "simple" and "mean–variance bias adjusted" slope homogeneity tests, respectively

Δ_{HAC} and $\left(\Delta_{HAC}\right)_{adj}$ represent the "Heteroskedasticity and Autocorrelation Consistent" versions of "simple" and "mean–variance bias adjusted" slope homogeneity tests, respectively

are not homogeneous, and heterogeneity exists in the relationship between the socio-economic development and carbon productivity across the sample countries. Consequently, based on the presence of heterogeneity, we employ heterogeneous panel techniques in our analysis.

4.3.2 Cross-Sectional Dependence Test

The study examines the cross-sectional dependence (CD) in the data based on the method developed by Pesaran [55, 61], Bailey et al. [62], and Xie and Pesaran [63]. We apply for the CD test because sample countries are connected in various ways, including culture, society, politics, and economics, which can lead to CD. CD means that the data from different countries may be related, often due to shared events, common policies, or effects that spread from one country to another [64]. If CD is present and not accounted for, it can result in biased results in the estimation process [55].

Table 3 shows the results of cross-sectional dependence for relevant variables and error correction term $\left(ln\_C_{i,t}, ln\_G_{i,t}, ln\_E_{i,t}, ln\_F_{i,t}, ln\_T_{i,t}, ln\_U_{i,t}, ECT\right)$. The findings indicate significant cross-sectional dependence in the variables and the residuals within our panel, hinting at the influence of unobserved common factors on carbon productivity across sample countries. These factors may include global economic shifts, international policies on reducing carbon emissions, or advances in technology [64]. Additionally, the transition towards a low-carbon economy exhibits national and regional differences, reflecting varied social, political, and economic settings [65]. Consequently, those estimation tools are selected that incorporate cross-sectional dependence in the estimation process.

Table 3 Tests for cross-sectional dependence

Test	Equation	$ln\_C_{i,t}$	$ln\_G_{i,t}$	$ln\_E_{i,t}$	$ln\_F_{i,t}$	$ln\_T_{i,t}$	$ln\_U_{i,t}$	ECT
CD_{NT}^{2015}	$\sqrt{\frac{2}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\frac{1}{\sqrt{T}}\sum_{t=1}^{T}\xi_{it}\xi_{j}$	37.03[a]	66.61[a]	58.65[a]	31.70[a]	65.21[a]	65.45[a]	23.36[a]
CD_{BKP}	$\sqrt{\frac{TN(N-1)}{2}}\hat{\rho}_N$	37.91[a]	67.75[a]	59.27[a]	33.41[a]	66.36[a]	66.61[a]	23.36[a]

[a]Statistical significance at 1%

Table 4 Second generation unit root tests

Cross-sectional ADF (CADF) test							
$ln\_C_{i,t}$	$\Delta ln\_C_{i,t}$	$ln\_G_{i,t}$	$\Delta ln\_G_{i,t}$	$ln\_E_{i,t}$	$ln\_F_{i,t}$	$ln\_T_{i,t}$	$ln\_U_{i,t}$
−1.518	−3.881***	−1.313	−4.740***	−2.572**	−2.128**	−4.691***	−4.506***
$C_{i,t}$ is $I(1)$		$Y_{i,t}$ is $I(1)$		$E_{i,t}$ is $I(0)$	$F_{i,t}$ is $I(0)$	$T_{i,t}$ is $I(0)$	$U_{i,t}$ is $I(0)$
Cross-sectional IPS (CIPS) test							
$ln\_C_{i,t}$	$\Delta ln\_C_{i,t}$	$ln\_G_{i,t}$	$\Delta ln\_G_{i,t}$	$ln\_E_{i,t}$	$ln\_F_{i,t}$	$ln\_T_{i,t}$	$ln\_U_{i,t}$
−1.807	−5.597***	−1.552	−5.369***	−3.087***	−2.595***	−5.343***	−5.373***
$C_{i,t}$ is $I(1)$		$Y_{i,t}$ is $I(1)$		$E_{i,t}$ is $I(0)$	$F_{i,t}$ is $I(0)$	$T_{i,t}$ is $I(0)$	$U_{i,t}$ is $I(0)$

By definition: $CIPS = \frac{\sum_{i=1}^{N} t_i(N,T)}{N} = \frac{\sum_{i=1}^{N} CADF_i}{N}$

*** and ** represent statistical significance at 1% and 5%, respectively

4.3.3 Panel Unit Root Test

To account for stationarity in the presence of cross-sectional dependence, we used second-generation unit root tests, specifically the Cross-Sectional Augmented Im, Pesaran and Shin (CIPS) and Cross-sectional Augmented Dickey-Fuller (CADF) tests developed by Pesaran [66–68] do not account for cross-sectional dependence when testing for stationarity. The equations for the CIPS and CADF unit root tests is given below:

$$\Delta y_{i,t} = a_i + b_i y_{i,t-1} + c_i \overline{y}_{t-1} + d_i \Delta \overline{y}_t + \varepsilon_{i,t}.$$

Where a_i is a deterministic term, $\overline{y}_t$ is the cross-sectional mean at time t, and ρ is the lag order, while $t_i(N,T)$ denotes the corresponding t-ratio of α_i and is known as cross-sectional ADF (CADF), attributed to Pesaran [66]. The average of the t-ratios gives the cross-sectional IPS (CIPS), attributed to Pesaran [69]. Table 4 estimates unit root tests with a constant term both at the level and first difference.

The findings of CADF and CIPS tests show a mixed order of integration, i.e., $\overbrace{[ln\_C_{i,t},\ ln\_G_{i,t},\ ln\_E_{i,t},\ ln\_F_{i,t},\ ln\_T_{i,t},\ ln\_U_{i,t}]}^{[I(1),\ I(1),\ I(0),\ I(0),\ I(0),\ I(0)]}$ The occurrence of mixed orders of integration can present challenges in econometric analysis. Nevertheless, our application of the cross-sectionally auto-regressive distributed lag model (CS-ARDL) is beneficial as this method is well-suited to manage variables with both first and mixed orders of integration [70]. This approach ensures the robustness of our econometric analysis in the face of the mixed integration properties of the dataset.

4.3.4 Panel Cointegration Analysis

To address the issue of slope heterogeneity, CD, and mixed order of integration among the variables, we apply the CS-ARDL model, attributed to Chudik & Pesaran [71], to examine the long-run and short-run relationship among C, Y, E, F, T, and U. The general equation for CS-ARDL is given as below:

$$D_{i,t} = \sum_{I=0}^{p_D} \vartheta_{I,i} D_{i,t-I} + \sum_{I=0}^{p_X} \delta_{I,i} X_{i,t-I} + \epsilon_{i,t}$$

To solve the issue of CD and slope heterogeneity, the extended version of the last equation is given as follows:

$$D_{i,t} = \sum_{I=0}^{p_D} \vartheta_{I,i} W_{i,t-I} + \sum_{I=0}^{p_X} \delta_{I,i} X_{i,t-I} + \sum_{I=0}^{p_Z} \sigma_i' I \overline{Z}_{t-I} + \epsilon_{i,t},$$

In the last equation, $\overline{Z}_{t-I} = \left(\overline{D}_{i,t\bar{I}}, \overline{X}_{i,t\bar{I}}\right)$ provides the averages; similarly, lags are shown through p_D, p_X, p_Z: D_{it} is the dependent variable (in this case ln_C), followed by $X_{i,t}$ for all the independent variables (here, ln_G, ln_E, ln_F, ln_T, and ln_U). $\overline{Z}$ is a dummy for the time. The long-run coefficients are generally represented as follows:

$$\hat{\theta}_{CS-ARDL,i} = \frac{\sum_{I=0}^{p_X} \hat{\delta}_{I,i}}{1 - \sum_{I=0}^{p_D} \hat{\vartheta}_{I,i}},$$

Whereas following equation shows the mean group coefficients:

$$\hat{\overline{\theta}}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\theta}_i,$$

Similarly, the short-run coefficients are expressed with the following four equations:

$$\Delta D_{i,t} = \vartheta_i\left[D_{i,t-1} - \theta_i X_{i,t}\right] - \sum\nolimits_{I=1}^{p_{D-1}} \vartheta_{I,i}, \Delta_I W_{i,t-I} + \sum\nolimits_{I=0}^{p_X} \delta_{I,i}\Delta_I X_{i,t} + \sum\nolimits_{I=0}^{p_Z} \sigma_i' I\overline{Z}_t + \varepsilon_{i,t},$$

$$\hat{\alpha}_i = -\left(1 - \sum\nolimits_{I=1}^{p_D} \hat{\vartheta}_{I,i}\right),$$

$$\hat{\theta}_i = \frac{\sum_{I=0}^{p_X} \hat{\delta}_{I,i}}{\hat{\alpha}_i},$$

$$\hat{\bar{\theta}}_{MG} = \sum\nolimits_{i=1}^{N} \hat{\theta}_i.$$

In CS-ARDL, error correction mechanism (*ECM*) should be statistically significant, as it shows the speed of adjustment towards equilibrium.

4.3.5 Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG)

The CS-ARDL model has been criticized for imposing a homogeneity restriction in the long-run, despite countries exhibiting varied economic and social structures. Therefore, as a robustness check of the obtained estimates by CS-ARDL, we used two additional models, CCEMG and AMG, that address CD by allowing parameter to be heterogeneous in the long run. Pesaran [72] forwarded CCEMG model with an estimator $\beta_j\left(= \beta + \omega_j\right)$ which implies a common parameter β across the countries, while $\omega_j \sim IID\left(0, V_\omega\right)$. CCEMG tends to eliminate CD asymptotically. Moreover, it allows heterogeneous slope coefficients across group members that are captured simply by taking the average of each country's coefficient [73].

Attributed to Eberhardt and Teal [74], AMG model is alternate to CCEMG, which also captures the unobserved common effect in the model. Moreover, the AMG estimator also measures the group-specific estimator and takes a simple average across the panel. The highlight of AMG is that it follows the first difference OLS for pooled data and is augmented with year dummies. The estimable model can be written as below:

$$ln\_C_{it} = \alpha_i + c_i t + d_i \hat{\mu}_t^{va\cdot} + \beta_{i,1}\left(ln\_G_{i,t}\right) + \beta_{i,2}\left(ln\_E_{i,t}\right) + \beta_{i,3}\left(ln\_T_{i,t}\right) + \beta_{i,4}\left(ln\_F_{i,t}\right) + \beta_{i,5}\left(ln\_U_{i,t}\right) + \varepsilon_{i,t}.$$

Where i stands for cross-sectional dimension $i = 1, \ldots, n$ and time period $t = 1, \ldots, t$ and α_i represents country-specific effects and $d_i t$ denotes heterogeneous country-specific deterministic trends. The α_i is related to the coefficient of respective independent variables $\beta_{i1} = \frac{\alpha_{i1}}{1-\alpha_{i1}}$, $\beta_{i2} = \frac{\alpha_{i2}}{1-\alpha_{i2}}$, $\beta_{i3} = \frac{\alpha_{i3}}{1-\alpha_{i3}}$, $\beta_{i4} = \frac{\alpha_{i4}}{1-\alpha_{i4}}$ and $\beta_{i5} = \frac{\alpha_{i5}}{1-\alpha_{i5}}$, that are considered heterogeneous across the countries. It is also assumed that the short-run dynamics and their adjustment towards the long run take place via error term $u_{i,t}$ $(= \acute{\Gamma}_i f_t + \varepsilon_{i,t})$. The f_t characterizes the vector of unobserved common shocks and can be either stationary or nonstationary, which does not influence the validity of the estimation [75]. The AMG estimation finds an explicit estimate for f_t which renders $\hat{\mu}_t^{va\cdot}$ (common dynamic process) economic meaningfulness. Total factor productivity (TFP) is one of the plausible interpretations of $\hat{\mu}_t^{va\cdot}$. It's coefficient d_i represents the implicit factor loading on common TFP. In addition, the cross-sectional specific errors $\varepsilon_{i,t}$ are permissible to be serially correlated over time and weakly dependent across the countries [76]. However, the regressors and unobserved common factors have to be identically distributed.

4.3.6 Panel Granger Non-causality Test

Although the CS-ARDL, CCEMG, and AMG provide reliable outcomes, they do not provide the direction of relationship between the selected variables, which is important for policy considerations. Hence, we utilize the novel approach by Juodis et al. [57] to explore the causal link between socio-economic development and carbon productivity. Juodis et al. [57] provided a superior version of the panel Granger Causality (1969) test for homogeneous or heterogeneous panels among more than two variables. This refined method adeptly addresses the issues of endogeneity and bidirectionality that often-complicate causal inference. Another superior version of the Granger Causality test is Dumitrescu and Hurlin [77], which also addresses CD and heterogeneity but overlooks "Nickell" bias.[1] Dhaene & Jochmans [78] developed the Half Panel Jackknife (*HPJ*) technique to avoid size distortion and correct parameter bias. The methodology adopted by Juodis et al. [57] incorporates HPJ, enhancing the reliability of panel data inference by allowing for the presence of CD. The model is specified given as follows:

$$y_{it} = \alpha_{0i} + \sum\nolimits_{p=1}^{P} \alpha_{pi} y_{it-p} + \sum\nolimits_{q=1}^{Q} \beta_{qi} x_{it-q} + \varepsilon_{it},$$

Where $i = 1, 2, ..., N$, $t = 1, 2, ..., T$, and $\varepsilon_{it} \sim N\left(0, \sigma^2\right)$. The N and T are the number of countries and times, correspondingly. In addition, α_{0i} shows the individual fixed effect, α_{pi} denotes autoregressive coefficient, and β_{qi} depicts Granger causation parameters or feedback coefficients that are heterogeneous.

Set $z_{it} = \left(1, y_{it-1}, ..., y_{it-P}\right)'$, $x_{it} = \left(1, x_{it-1}, ..., x_{it-Q}\right)'$, $\alpha_i = \left(\alpha_{0i}, ..., \alpha_{Pi}\right)'$, $\beta_i = \left(\beta_{1i}, ..., \beta_{Qi}\right)'$, $y_i = \left(y_{i1}, ..., y_{iT}\right)'$, $\varepsilon_i = \left(\varepsilon_{i1}, ..., \varepsilon_{iT}\right)'$. So, y_i can be reiterated, in vector form, as follows:

$$y_i = Z_i \alpha_i + X_i \beta_i + \varepsilon_i,$$

[1] For standard estimation test, it is hard to control asymptotic size.

Where $Z_i = \left(z_{i1}, \ldots, z_{iT}\right)$ shows a matrix of $[T \times (1 + P)]$ and $X_i = \left(x_{i1}, \ldots, x_{iT}\right)$ represents a matrix of $[T \times Q]$. It is assumed that β_i is homogeneous since the real coefficient vector of X_i is equal to zero under the H_0. Thus, y_i becomes:

$$y_i = Z_i\alpha_i + X_i\beta + \varepsilon_i,$$

Juodis et al. [57] calculated the coefficient β, for the solution of the parameter bias:

$$\widetilde{\beta} \equiv 2\widehat{\beta} - \frac{1}{2}\left(\widehat{\beta}_{1/2} + \widehat{\beta}_{2/1}\right) = \widehat{\beta} + \left\{\widehat{\beta} - \frac{1}{2}\left(\widehat{\beta}_{1/2} + \widehat{\beta}_{2/1}\right)\right\},$$

Where β, $\widehat{\beta}_{1/2}$, and $\widehat{\beta}_{2/1}$ portray the estimation of β coefficient via fixed effects estimation for cases of $T_1 = T, T_2 = \frac{T}{2}$ and $T_3 = T_1 - T_2$, correspondingly. The final component is "Nickell" bias.

The H_0 is that there is no Granger causality in any cross-section. Accordingly, H_A is that the Granger causality exists in at least one cross-section:

$$\left(H_0 : \forall\beta_i = 0, i = 1, 2, \ldots, N; H_1 : \exists\ \beta_i \neq 0, i = 1, 2, \ldots, N\right).$$

HPJ-Wald statistic is as follows:

$$\widehat{W}_{HPJ} = NT\widetilde{\beta}'\left(\widehat{J}^{-1}\widehat{V}\widehat{J}^{-1}\right)^{-1}\widetilde{\beta} \xrightarrow{d} \chi^2(Q),$$

Where $J = \frac{1}{NT}\sum_{i=1}^{N} X_i' M_{Z_i} X_I$, $M_{Z_i} = I_T - Z_i\left(Z_i'Z_i\right)^{-1}Z_i'$, $\widehat{V} = \widehat{\sigma}^2\widehat{J}$, and $\widehat{\sigma}^2 = \frac{1}{N(T-1-P-Q)}\sum_{i=1}^{N}(yi - Xi\beta)'M_{Z_i}\left(y_i - X_i\widehat{\beta}\right)$. Also, $\widehat{W}_{HPJ}$ adheres the χ^2 distribution of Q.

5 Results and Discussion

This section presents the main results and findings of the empirical outcomes gathered from our estimation techniques and analysis, which include CS-ARDL estimates, robustness checks using CCEMG and AMG, country-specific results, and panel Granger non-causality findings. This followed by an in-depth interpretation that contextualizes these results within the existing body of literature and theoretical framework.

5.1 CS-ARDL Estimates

The results of the CS-ARDL estimation, presented in Table 5, support the hypothesis that socio-economic development significantly affects carbon productivity both in short run and long run. The findings show that GDP per capita, FDI, and trade are the push factors, which means that these factors have a positive and statistically significant influence on carbon productivity. In another sense, it means that these indicators play a significant role in promoting carbon productivity. The findings are consistent with the findings of previous studies conducted in different regions (e.g., [22, 28, 47, 54]), which found a positive and significant impact of GDP per capita, FDI, and trade on carbon productivity. For instance, socio-economic factors such as GDP per capita, trade, and FDI can improve carbon productivity through the composition effect, technique effect, and by introducing innovative technologies [47]. Wang et al. [20] argued that higher GDP per capita often correlates with greater technological advancements and efficiency, potentially increasing carbon productivity. Additionally, EKC suggests that when GDP per capita crosses the threshold level, environmental quality improves due to a shift to a knowledge-based economy [28]. Moreover, trade openness and FDI can facilitate the transfer of cleaner technologies and sustainable practices across borders, enhancing carbon efficiency [21, 22]. According to the Pollution Halo hypothesis, FDI can bring positive changes in the environmental management system and introduce environmentally friendly technology in the host country. Green technology will replace obsolete technology, which will reduce pollution and promote environmentally friendly practices that will help increase carbon productivity [54]. Furthermore, trade can benefit the environment as it serves as an engine of technological progress due to the technological spillovers it generates. In an open economy, technological progress also depends on technological spillovers other than domestic research and development spending [22].

Conversely, the results show that energy use and urbanization are pull factors, which means that these factors have a negative relationship with carbon productivity. The findings reveal that energy use significantly negatively affects carbon productivity both in the short run and the long run,

Table 5 CS-ARDL estimation results

Variables	Long run estimates	Short run estimates
$ln\_G_{i,t}$	0.884*** (0.164)	0.062** (0.032)
$ln\_F_{i,t}$	0.256** (0.101)	0.166** (0.120)
$ln\_T_{i,t}$	0.122** (0.056)	0.154 (0.111)
$ln\_E_{i,t}$	−0.173*** (0.032)	−0.067** (0.037)
$ln\_U_{i,t}$	−0.067* (0.037)	−0.070 (0.074)
ECM (-1)	−0.188*** (0.056)	

Dependent variable: $ln\_C_{i,t}$

***, **, and * show statistical significance at 1%, 5%, and 10%, respectively

Parentheses contain standard errors

while urbanization influences carbon productivity only in the long run with weak statistical significance. The findings are consistent with the findings of previous studies conducted in a similar environment (e.g., [7, 23, 24, 52]. For instance, it is argued that high energy consumption, particularly from non-renewable sources, and rapid urbanization can lead to increased emissions, thereby reducing carbon productivity [23, 24]. Similarly, increased energy consumption negatively impacts environmental quality through the use of energy-intensive industries and infrastructure. Moreover, in most countries, electricity production is mainly fueled by coal and other non-renewable sources [7]. Consequently, the burning of fossil fuels increases CO2 emissions which reduces carbon productivity. In a similar way, increasing urbanization has a negative impact on the environment. Zhou et al. [52] explain that as urbanization continues its rapid expansion, demand for energy and resources from industries and other economic sectors grows significantly and places immense strain on existing infrastructure, leading to congestion, inadequate transportation systems, and overwhelmed utilities such as water and sanitation. Moreover, the uncontrolled growth of urban areas contributes to environmental degradation through land use changes and encroachment on agricultural land, deforestation, and increased pollution from industrial activities and transportation [53].

Besides, the $ECM(-1)$ value show that around 19% of any disequilibrium in the relationship between the variables is corrected every year. This highlights the dynamic adjustment process in the relationship between socio-economic development and carbon productivity. Therefore, our CS-ARDL results provide robust evidence for the impact of socio-economic development on carbon productivity in the top 18 carbon-emitting countries. This underscores the critical role of sustainable economic practices, effective management of trade, FDI, and urbanization in enhancing carbon productivity. This holistic approach is essential for fostering long-term economic resilience and sustainable development, aligning with global climate action goals outlined in SDG 13.

5.2 Robustness Check using CCEMG and AMG Estimators

Table 6 presents the findings of CCEMG and AMG estimators. Upon checking the results of CCEMG and AMG, we noticed that findings from these estimators are generally in line and stable with those obtained from CS-ARDL estimations and support the robustness of our results. Additionally, these strengths the reliability and validity of our CR-ARDL estimations and reinforces the confidence in the relationship observed among explanatory variables and carbon productivity. Moreover, under AMG estimates, the common dynamic process (CDP) is statistically significant at 5%, with $\widehat{\mu}_t^{va\cdot} = 0.143$. This significance can be attributed to shared policies, regional and international agreements, and the diffusion of technological innovations among the top 18 carbon-emitting countries [51]. These factors collectively contribute to achieving higher levels of carbon productivity, highlighting the importance of coordinated efforts in addressing climate change and promoting sustainable economic growth.

Table 6 CCEMG and AMG estimation results

Variables	CCEMG	AMG
$ln\_G_{i,t}$	0.293** (0.118)	0.159** (0.074)
$ln\_F_{i,t}$	0.247** (0.102)	0.303** (0.150)
$ln\_T_{i,t}$	0.641* (0.373)	0.214* (0.116)
$ln\_E_{i,t}$	−1.002** (0.470)	−0.148** (0.066)
$ln\_U_{i,t}$	−0.543** (0.244)	−0.595** (0.272)
Constant	0.956** (0.467)	0.026*** (0.008)
CDP	-	0.143** (0.058)

Dependent variable: $ln\_C_{i,t}$

***, **, and * show statistical significance at 1%, 5%, and 10%, respectively

CDP common dynamic process. Parentheses contain standard errors

5.3 Country Specific Effects

Table 7 shows the country-specific slopes for carbon productivity. Notably, 83% of the sample countries exhibit expected positive relationships, indicating that socio-economic development positively impacts carbon productivity in these nations. This suggests that these countries can serve as models for implementing effective low-carbon policies. Countries such as Australia, China, France, Germany, Indonesia, Italy, Japan, Poland, South Africa, South Korea, Spain, the UK, and Ukraine demonstrate significant positive effects, aligning with their advanced status and emphasis on green growth and sustainable development [79].

Conversely, Brazil, India, and Mexico show unexpected negative coefficients, indicating challenges in achieving carbon productivity improvements. This might be due to lower levels of energy use and their moderate rankings on the green growth index [80]. Kazakhstan and Saudi Arabia exhibit inconclusive results, possibly due to their lower energy use and less focus on green growth policies. The statistical significance at 1%, 5%, and 10% levels for most

Table 7 Country-specific effects

Country	β_i	Country	β_i
Expected country specific effects			
Australia	5.492***	Poland	3.991***
	(1.788)		(1.185)
China	4.330***	South Africa	7.423***
	(1.291)		(2.544)
France	4.772***	South Korea	5.481***
	(1.289)		(1.594)
Germany	9.644***	Spain	8.791***
	(2.673)		(2.442)
Indonesia	7.325***	UK	9.593***
	(2.225)		(2.836)
Italy	0.989**	Ukraine	2.991**
	(0.417)		(1.185)
Japan	2.900[a]	–	–
Unexpected country specific effects			
Brazil	– 3.492*	Mexico	– 0.332*
	(1.789)		(0.187)
India	– 1.972***	–	–
	(0.671)		
Inconclusive expected country specific effects			
Kazakhstan	1.574	Saudi Arabia	2.276
	(1.435)		(1.391)

country specific slopes (β_i)

***, **, and * show statistical significance at 1%, 5% and 10%, respectively. Standard errors are in parenthesis

countries underscores the robustness of these findings, emphasizing the varying impact of socio-economic factors on carbon productivity across different national contexts.

5.4 Panel Granger Non-causality

The results described in Table 8 show the panel Granger non-causality test, exploring the relationship between socio-economic development and carbon productivity. The estimation is completed with cross-sectional heteroskedasticity-robust standard errors. The findings reveal that GDP per capita and FDI have a feedback effect on carbon productivity, while trade exhibits a uni-causal relationship with carbon productivity. These results align with Rajbhandari and Zhang [81], who found causality from carbon intensity to GDP growth, and Long et al. [21], who identified a positive effect of FDI on carbon productivity. The uni-causal relationship between trade and carbon productivity is supported by Feng et al. [82], who found that trade significantly increases carbon productivity, and Zhang et al. [83], who confirmed that import trade boosts carbon productivity in China.

Additionally, the findings indicate that energy consumption has a feedback effect on carbon productivity, while urbanization shows a uni-causal effect. The uni-causality from urbanization to carbon productivity suggests that the expansion of urban centers corresponds to a significant increase in CO2 emissions. This finding is consistent with

Table 8 Panel Granger non-causality test results

Causality	$\widehat{W}_{HPJ}$	*Coef*	Results	Remarks
$G_{i,t} \rightarrow C_{i,t}$	6.047**	0.177** (0.072)	Causality from *G* to *C*	Bi causality
$C_{i,t} \rightarrow G_{i,t}$	14.191***	1.119*** (0.297)	Causality from *C* to *G*	
$F_{i,t} \rightarrow C_{i,t}$	23.503***	0.084*** (0.017)	Causality from *E* to *C*	Bi causality
$C_{i,t} \rightarrow F_{i,t}$	64.849***	0.333*** (0.041)	Causality from *C* to *E*	
$T_{i,t} \rightarrow C_{i,t}$	2.779*	0.246* (0.147)	Causality from *T* to *C*	Uni-causality from *T* to *C*
$C_{i,t} \rightarrow T_{i,t}$	0.420	0.110 (0.170)	No Causality from *C* to *T*	
$E_{i,t} \rightarrow C_{i,t}$	48.952***	– 1.034* (0.148)	Causality from *E* to *C*	Bi causality
$C_{i,t} \rightarrow E_{i,t}$	10.306***	– 0.135*** (0.042)	Causality from *C* to *E*	
$U_{i,t} \rightarrow C_{i,t}$	5.062**	– 0.560** (0.249)	Causality from *U* to *C*	Uni-causality from *U* to *C*
$C_{i,t} \rightarrow U_{i,t}$	0.303	0.231 (0.42)	No Causality from *C* to *U*	

***, **, and * show statistical significance at 1%, 5% and 10% respectively. Parentheses contain standard errors

$\widehat{W}_{HPJ}$ Wald statistic Half Panel Jack-knife estimator

Liu et al. [23] and Jahanger et al. [84], who found similar mechanisms for urbanization and carbon productivity. The robustness of these results is ensured by accounting for heteroskedasticity across sections, providing more accurate and reliable inferences. The statistical significance further strengthens the validity of the findings. In essence, the findings highlight the significant impact of socio-economic factors on carbon productivity and underscore the necessity for integrated policies that promote sustainable economic growth while mitigating carbon emissions.

6 Conclusion and Recommendations

This study embarked on an in-depth exploration of the relationship between socio-economic development and carbon productivity in the top 18 CO2-emitting countries, aligning closely with the SDGs, particularly SDG 13: Climate Action. The objective is to test the hypothesis that socio-economic development factors—such as GDP per capita, trade, FDI, energy consumption, and urbanization—affect carbon productivity over the period from 1990 to 2019. Using a panel dataset, we applied advanced econometric techniques, including the CS-ARDL, CCEMG, and AMG estimations, along with novel Granger non-causality tests, to ensure a comprehensive robust analysis. Our findings from the CS-ARDL model reveal that GDP per capita, trade, and FDI positively influence carbon productivity, highlighting the role of economic growth and international investment in enhancing environmental efficiency. Conversely, energy consumption and urbanization were found to negatively impact carbon productivity, emphasizing the need for cleaner energy sources and sustainable urban planning. The robustness checks using CCEMG and AMG estimators confirmed these results, underscoring their reliability and consistency across different estimation techniques. The country-specific effects analysis indicated that 83% of the sample countries exhibit positive relationships between socio-economic development and carbon productivity, suggesting that these nations can serve as models for effective low-carbon policies. However, countries like Brazil, India, and Mexico showed negative coefficients, pointing to specific challenges in improving carbon productivity. The panel Granger non-causality tests further supported these findings, demonstrating bi-directional relationships for GDP per capita, FDI, and energy use with carbon productivity and uni-causal relationship for trade and urbanization.

The findings of this study highlight several important policy implications for enhancing carbon productivity and promoting sustainable development. Firstly, policymakers should focus on promoting economic growth that incorporates technological advancements and increased efficiency, as higher GDP per capita was found to positively influence carbon productivity. Investments in green technologies and innovation are essential to achieving this goal. Secondly, trade openness and FDI play key roles in transferring cleaner technologies and sustainable practices across borders. Therefore, policies that facilitate international trade and attract environmentally friendly foreign investments should be prioritized. Thirdly, to address the negative impact of energy consumption on carbon productivity, countries must transition to renewable energy sources such as wind, solar, hydro, and nuclear power. Governments should implement policies that incentivize the adoption of renewable energy technologies and improve energy efficiency in both industrial and residential sectors. Fourthly, the detrimental effect of urbanization on carbon productivity necessitates sustainable urban planning and development strategies. Policymakers should promote energy-efficient infrastructure, public transportation systems, and green spaces to mitigate the environmental impact of urban expansion. Last but not least, international cooperation is important for sharing best practices and technologies to improve carbon productivity globally. Countries should collaborate on research and development initiatives, exchange knowledge on sustainable practices, and participate in international agreements that aim to reduce carbon emissions.

Although this study is comprehensive, it has some limitations that should be addressed in future research. Firstly, the analysis is confined to the top 18 CO2-emitting countries, which limits the generalizability of the findings to other nations with different socio-economic and environmental contexts. Future studies should expand the scope to include a broader range of countries, particularly those with emerging economies and varying levels of industrialization. Secondly, the time span of this study is before the COVID-19 pandemic, which limits the relevance of the findings to the current context and may not fully capture recent changes and trends in socio-economic factors and carbon productivity. The pandemic has brought about unprecedented changes in global economic activity, energy consumption patterns, and industrial operations, all of which are important factors influencing carbon productivity. The decision to focus on the period before COVID-19 was made to ensure data consistency and avoid the volatile disruptions caused by the pandemic. However, it is essential for future research to investigate the impacts of COVID-19 and the post-pandemic recovery period on socio-economic factors and carbon productivity. This would provide a more comprehensive understanding of how such global disruptions affect environmental efficiency and economic sustainability. Finally, the impact of other potential factors such as policy changes, technological advancements, and social behaviors on carbon productivity could be explored in more detail. By addressing these limitations, future research can build on the findings of this study to develop more comprehensive and nuanced strategies for increasing carbon productivity and achieving sustainable development goals.

Abbreviations *AGGI*: Annual Greenhouse Gas Index; *AMG*: Augmented mean group; *CADF*: Cross-sectional augmented Dickey-Fuller; *CIPS*: Cross-sectional augmented IPS; *CS-ARDL*: Cross-sectionally augmented autoregressive distributed lag; *CCEMG*: Common correlated effects mean group; *CD*: Cross-sectional dependence; *CO2*: Carbon dioxide; *ECM*: Error correction mechanism; *ECT*: Error correction term; *EKC*: Environmental Kuznets curve; *FDI*: Foreign direct investment; *GDP*: Gross domestic product; *GHG*: Greenhouse gas; *HDI*: Human development index; *HPJ*: Half Panel Jackknife; *IPCC*: Intergovernmental panel on climate change; *NOAA*: National Oceanic and Atmospheric Administration; *OECD*: Organisation for Economic Co-operation and Development; *SDG*: Sustainable development goals; *TFP*: Total factor productivity

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Declarations

Ethics Approval Not applicable.

Competing Interests The authors declare no competing interests.

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